URBAN ROAD ACCIDENTS AND RIDEHAILING SERVICES: A STUDY OF DEPENDENCE IN MADRID

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ABSTRACT

Few studies have examined whether there is an association between these services and traffic accidents, and virtually all of the existing studies focus in cities of United States. In this study, we analyse the impact of ridehailing services on traffic accidents with at least one young person dead or seriously injured (16-39 years old) in the municipality of Madrid from 2014 to 2018. To do this, a regresion analysis has been carried out using a Random-Effects Negative Binominal Regression (RENB). The results of the model show that Uber and Cabify services are related to a reduction in urban accidents.

1. INTRODUCTION

Traffic accidents are one of the world´s leading causes of death among children and young people between the ages of five and twenty-nine. Around 1.35 million people per year die as a result of a traffic accident. Furthermore, between 20 and 50 million people involved in traffic accidents sustain injuries which, in many cases, result in a disability (World Health Organization, 2018).

In Spain, 1.755 people died in traffic accidents, according to the final balance of the General-Directorate for Traffic (2020). This figure includes people who died on interurban and urban roads during the 30 days following the accident. On urban roads, there were 519 deaths, 6% more than in 2018. Cities accounted for 30% of all deaths, the highest percentage since records have been kept.

The emergence of “ridehailing” platforms, such as Uber, which operates in more than 630 cities in 80 countries around the world (Uber, 2020), or Cabify, which is present in 11 countries and more than 90 cities in the world (Cabify, 2020), can improve the supply in demand segments that previously had difficulties to access taxis, thereby reducing road traffic-related deaths and injuries.

Despite the fact that two of Uber's top five markets are located outside of the United States, and that the majority of ridehailing trips worldwide occur beyond US borders, most studies of the relationship between the advent of Uber and road accidents have focused on the United States. Research from the United States has produced mixed findings, with some research observing a decline in at least some types of traffic fatalities following the rollout of Uber, but with other studies finding evidence for either no effect of Uber or even an increase in fatalities (Kirk et al., 2019; Barrios et al., 2019; Greemwood and Wattal, 2017; Martin-Buck, 2017; Peck, 2017; Dills and Mulholland, 2018; Morrison et al., 2018; Brazil and Kirk, 2016).

Most of these studies have analysed the impact of these services on alcohol-related road accidents. For example, A report by MADD (Mothers Against Drunk Driving) shows that this type of services offers positive results in terms of road safety: young people prefer to use this service as a designated driver instead of trying to drive themselves home after they had too much to drink.

The study results are also supported by other data: after UberX launched in cities across California, monthly alcohol-related crashes decreased by 6.5 percent among drivers under thirty (Flor et al., 2020).

Although alcohol consumption is one of the main causes of death in road accidents, this study focuses on Madrid, and ask whether the deployment of ridehailing services, as Uber or Cabify, has been associated with a significant change in the number of traffic accident fatalities and seriously injuries related young people, whether or not they have consumed alcohol.

If ridehailing yields declines in traffic fatalities and seriously injuries in Madrid and beyond, it may be advantageous for cities to partner with ridehailing companies to promote its use. Conversely, if ridehailing actually increases the risk of road accidents and fatalities, it may be advisable for cities to be cautious in their licensing and regulations with respect to ridehailing (Kirk et al., 2020).

2. METHODS

To analyse the impact of ridehailing platforms on traffic accidents in Madrid, the authors had to face two main challenges.

On the one hand, in a big city like Madrid, with more than 3 million inhabitants, there are large geographical contrasts. For this reason it was necessary to analyse performance by districts.

On the other hand, to carry out an indeph study of the traffic accidens, with young victim, ocurred in the period from 2014 to 2018.

It is also necessary to know the impact of Uber and Cabify as well as the evolution of other socio-economic factors on accident rates. To this end, it was decided to carry out a spatio-temporal analysis to establish a comparative analysis between the accident rate in the previous years to the implementation of these services and the years thereafter.

2.1 Sample

We used an observational panel study design to examine within-district changes in traffic accident fatalities and seriously injuries related young people before and after implementation of Uber and Cabify services for the period from 2014 to 2018. The analytic sample contained yearly observations of each of the 21 district of Madrid (Fig.1).

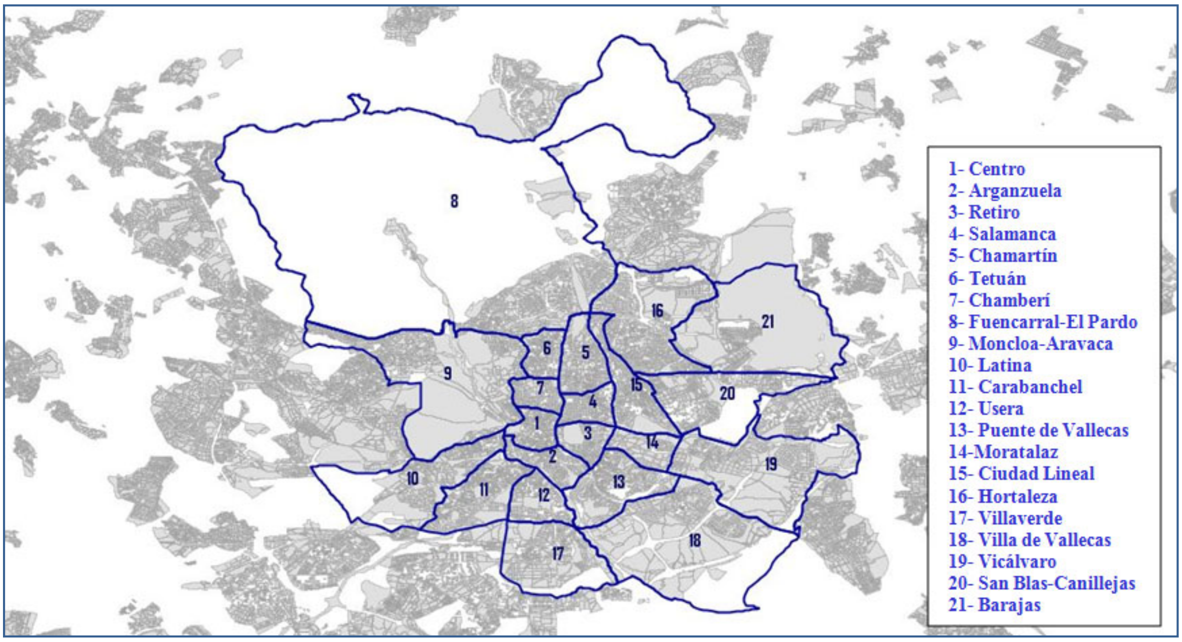

Figure 1: Map of the 21 districts of Madrid. Source: own research.

2.2 Dependent variable

According to the study carried out by Young and Farber (2019) in the city of Toronto, with regard to age, ridehailing users tend to be younger than average, and to be most often aged between 20 and 39 years old. Despite there being slightly more 30-39 than 20-29 years old ridehailing users, raidhailing trips made by 20-29 years old represent 2% of all trips conducted by individuals in this age group, which is more than double the share of raidhailing trip overall, making this age group the most likely to use radehailing service.

For this reason, in this study we wanted to analyse what has happened to accidents with victims in these age groups since the arrival of Uber and Cabify in Madrid. As all kinds of traffic accident variables have been considered, the dependent variables are divided into two separate group. In the first group, the age range for young victims cover from 15 years, in the case of involved moped accidents, up to 29 years.

The second group includes young victims from 30 to 39 years old. The two dependents variables measured for each of the 21 districts of Madrid are:

- total accidents with at least one fatality or serious injury between 15 and 29 years of age
- total accidents with at least one fatality or serious injury between 30 and 39 years of age

During the period from 2014 to 2018, a total of 2.182 accidents, with at least one young people death or seriously injured, were recorded (Fig.2). These data have been obtained from the City Council of Madrid which regularly publishes road accident data of the city and was produced by the Municipal Police. Each file includes a record for each person involved in the accident (drivers, passengers, pedestrians, witnesses, etc.), the type of accident (double collision, multiple collision, pedestrian impact, etc.), the time of the accident, the district, the street, the meteorological factors and the harm caused.

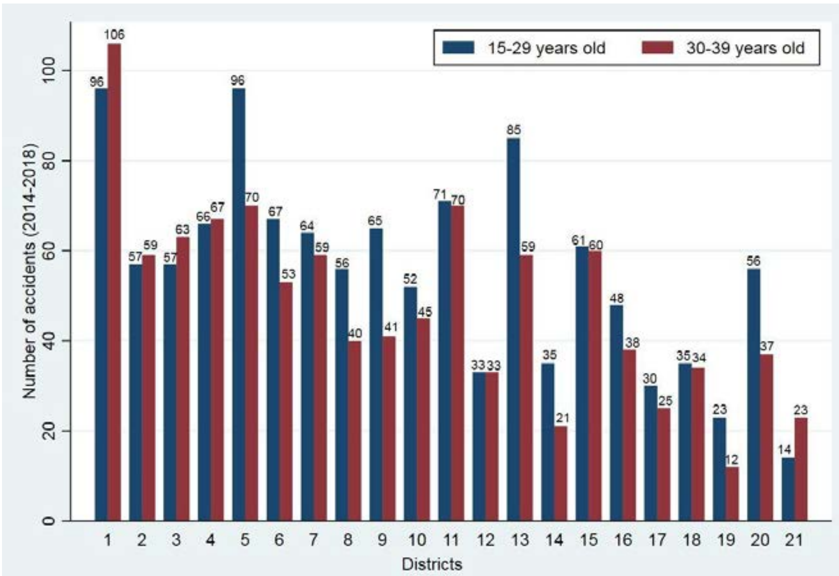

Figure 2: Crash count distribution in each district of Madrid. Source: own research.

2.3 Independent variable

The measure of Uber and Cabify deployment is a binary indicator of whether, in a given year, Uber or Cabify had established services in Madrid.

Cabify arrives in Madrid in 2011. Although it may seem logical to consider years prior to 2014 for this study, 2016 has been considered as the first year in which these services have been operating in the city of Madrid for two main reason:

- Uber arrives in Madrid in 2016
- In the case of Spain, the companies running the ride-hailing platforms Uber and Cabify recorded a considerable increase in revenues from 2015 onwards (Fig. 3).

The revenues of these companies in previous years reflect that the weight of these platforms might not be significant, as they were not yet well known among users.

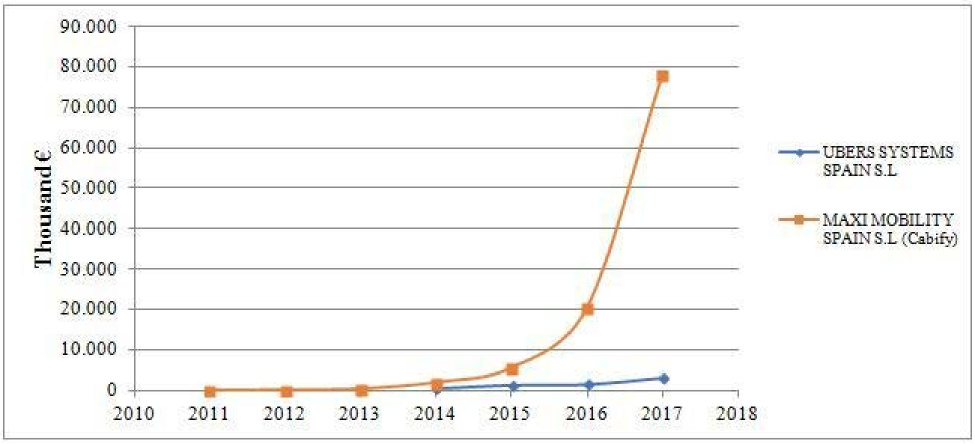

Figure 3: Evolution of Uber and Cabify income in Spain. Source: own research.

It has also been considered relevant to take into account other factors associated with crash risk. In previous studies, investigators found evidence that population influenced the rate of driver fatalities (Kirk et al., 2020). Dumbaugh and Rae (2009) studied how urban form—specifically land use and street network configurations— may influence the incidence of traffic-related crashes injuries and deaths in the City of San Antonio (Texas, USA).

The results showed that specific types of commercial land uses, such as big box stores, are related to a higher risk of accidents. Therefore, for this analysis we have taken into account the number of leisure establishments per district as points of attraction for drivers. We have also taken into account the density metro/cercanias station per district (equation 1), as a if young people do not have their own vehicle or a metro/cercanias station nearby, they may be captive to these services, generally cheaper than taxis. These data have been obtained from the City Council of Madrid publishes in its open data bank.

$$Density\ Urban\ Transport = Population/Number\ of\ metro\ stations \qquad (1)$$

Table 1 shows a summary of the variables considered in this analysis.

Variables	Definition
Total accidents (15-29 years old)	Number of total accidents in each district of Madrid with at least one fatality or serious injury between 15 and 29 years of age
Total accidents (30-39 years old)	Number of total accidents in each district of Madrid with at least one fatality or serious injury between 30 and 39 years of age
Population	Number of people registered in each district
Leisure Establishments	Number of premises dedicated to the catering, leisure and entertainment activities
Density Metro/Cercanias Stations	Indicator calculated from the population of each district and the number of metro/cercanias stations.
Ridehailing	Year dummy variables 1: Uber or Cabify presence 0: neither Uber nor Cabify

Table 1. Explanatory variables. Source: own research.

2.4 Modelling urban traffic accidents

Models such as the Poisson regression, the Negative Binomial (NB), the Zero-inflated Negative Binomial (ZINB) or Multivariate analysis are frequently applied for statical analysis at the section level, but limitations in the available methodology should be tested (Lord and Mannering´s, 2010).

Considering the Madrid database of the study, over-dispersion affects the registered data corresponding to road accidents. This is one notable characteristic of crash-frequency data: the variance exceeds the mean of the crash counts, and indicates that the most common count-data modelling approach (the Poisson regression model) cannot be used.

Consequently, the most common models applied with over-dispersion and cross-sectional data are the Negative Binomial model and the Zero-Inflated Negative Binomial or ZINB model. The latter is applied when the database has a large number of zero-crash observations, thus the most appropriate model for this case is Negative Binomial, which can account for overdispersion (Casares et al., 2019).

Moreover, temporal analysis has to be included in the modelling. In other words, information has been gathered from several individuals (districts) in a given moment during various periods of time (series of years) and the best of way of processing this data is by using a cross-sectional panel data structure.

Therefore, the multivariate analysis cannot be used. As a result, the most common models applied with cross-sectional data and in the case of over-dispersion are the Negative Binomial model and the Zero-inflated Negative Binomial or ZINB model. The latter is applied when the database has a large amount of zero shock observations, so the most appropriate model for this case is the Negative Binomial model, which can explain the excessive dispersion.

However, in this case, and as we have previously seen, the accident data have been collected from 21 districts over a period of five years, which means that the data could have specific location effects and it is likely that they are serially correlated.
If there are spatial effects in the data that cannot be considered as such, the estimated standard deviations of the regression coefficients will be underestimated, as each observation actually contributes less information than the real one (Chin and Quddus, 2003). For this reason, it was decided to consider the Random-Effects Negative Binomial Model (RENB).

3. RESULTS

As previously mentioned, the study was conducted using data corresponding to the period between 2014 and 2018. Table 2 provides descriptive statistics of the variables.

	Obs	Maximum	Minimum	Standard Deviation	Mean
Dependent variables					
Total accidents (15-29 years old)	105	27	2	5,67	11,11
Total accidents (30-39 years old)	105	24	0	5,26	9,67
Independent variables					
Population (per 1.000)	105	253,433	45,95	54,11	152,67
Leisure Establishments (per 1.000)	105	3,22	0,058	0,61	0,86
Density Urban Transport	105	29.800,8	6.028,14	7.177,76	14.256,78
Ridehailing	105	1	0	0,49	0,6

Table 2: Descriptive statistics. Source: own research.

Both models are statistically significant as shown in Table 3. The ridehailing services variable is statistically significant with a negative coefficient in model 2, showing that the entry of ridehailing services has reduced young casualty crashes aged 30-39 years old.

	Dependent variables	
	Model 1	**Model 2**
Independent variables	**Total accidents (15-29 years old)**	**Total accidents (30-39 years old)**
Population	0.00379** (3.20)	0.00338** (2.89)
Density Urban Transport	-0.0000158 (-1.71)	-0.0000194* (-2.13)
Leisure Establishments	0.275** (2.80)	0.358*** (3.78)
Ridehailing	-0.0789 (-1.07)	-0.215** (-2.94)
Ln_r Ln_s	4.407*** (7.50) 3.649*** (5.77)	5.020*** (6.66) 3.676*** (5.11)
Log-likelihood with constant only	-325.5092	-317.26
Log-likelihood at convergence	-297.60511	-281.98443
Ratio of log-likelihood index (ρ^2) and adjusted log-likelihood index (ρ^{-2})	0.091, 0.074	0.111, 0.10
Prob > chisq	0.0000***	0.0000***
LR test vs. pooled: chibar2(01), Prob>=chibar2	7.05, 0.004	4.69, 0.015
Hausman Test: chi2(8), Prob > chi2	4.87, 0.3012>0.05	6.67, 0.1547>0.05
***Significant at 0.001 level **Significant at 0.01 level *Significant at 0.05 level		

Table 3: Results of the estimated model (z-statistics in parentheses). Source: own research.

As for leisure establishments, this variable is significant with a positive coefficient in both models, which means that there is a strong relationship between agglomerations of leisure venues (restaurants, pubs, theatres, cinemas...) and a higher concentration of accidents with young people seriously injured or killed in the municipality of Madrid. With respect to the influence of the population on traffic accidents, this variable is also statistically significant with a positive coefficient in the two models, which shows that a higher level of population generates more traffic and, as a result, gives rise to an increase in traffic accidents, in the same way as in the study carried out by Casares *et al.* (2019). With respect to Density Urban Transport this variable is significant with a negative coefficient in Model 2, indicating that a higher number of metro stops decreases accidents with young people 30 to 39 years old.

4. CONCLUSIONS

The findings presented in this study reveal that the arrival of ride-hailing services in the Madrid municipality is related to the decrease in accidents with seriously injuries or deaths with young people aged between 30 and 39 years. The analysis also shows that metro stations decreases road traffic fatalities and serious injuries in this group of young people. Furthermore, population, as well as the presence of leisure establishment, increase traffic accidents with young people.

Finally, this study has only considered the traffic accidents with at least one person dead or seriously injured with young people aged betweeen 15 and 39 years. But it is very interesting to analyze what happens with other types of accidents. That is why, at present, this line of investigation continues and it is being analyzed how others variables and the presence of Uber and Cabify affect the 21 districts of Madrid, considering other kinds of road accident variables.

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